Electronic Markets (2025) 35:77
https://doi.org/10.1007/s12525-025-00821-8

RESEARCH PAPER

Optimizing AI strategies in e-commerce customer service: An agent-based simulation

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Received: 17 October 2024 / Accepted: 4 August 2025 / Published online: 4 September 2025

Abstract
The growing integration of chatbots in e-commerce customer service presents opportunities and challenges for online retailers in shaping effective artificial intelligence (AI) strategies. This study evaluates human-only, AI-only, and human–AI collaboration strategies using an agent-based simulation model across varying levels of task complexity, service volume, and product margin. Results show that the AI-only strategy excels in low-volume, simple tasks due to its cost-effectiveness, while the human–AI collaboration strategy proves superior in managing high-volume or complex inquiries by scaling human involvement to meet demand. For high-margin products, this collaborative approach delivers the best service, whereas the AI-only strategy is optimal for low-margin items. Enhancing chatbots' anthropomorphic qualities could further improve service performance, but only if technological advancements are sufficient. The findings provide actionable insights for optimizing AI deployment and fostering adaptive customer service.

Keywords Platform e-tailer · Online customer service · Human–AI collaboration · Request subjectivity · Time sensitivity · Agent-based simulation

JEL classification C63 · L81 · M31

Introduction

E-commerce platforms serve as key channels for retailers to deliver online customer service, significantly influencing consumer satisfaction and retention (Sun et al., 2021).

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Advances in artificial intelligence (AI), particularly large language models (LLMs), have expanded the use of chatbots in this domain (Krüger et al., 2024). Compared to human representatives, chatbots offer fast, simultaneous responses while reducing operational costs for platform electronic retailers (e-tailers). According to Grand View Research, the AI chatbot market was valued at USD 6.31 billion in 2023 and is projected to reach USD 27.30 billion by 2030, with the service sector driving this growth (Grand View Research, 2023).

Optimizing the allocation of human and AI services poses a significant challenge for platform e-tailers. Chatbots offer a cost-effective solution for straightforward tasks, efficiently serving multiple customers simultaneously without delays. However, they often fall short of customer expectations for more complex issues. Despite advancements, even state-of-the-art LLMs struggle with language nuances (Mitchell & Krakauer, 2023) and accuracy (Forbes, 2023), and are further constrained by limited knowledge bases (Leggatt & Riva, 2023), particularly in e-commerce settings (Adam et al., 2020). In contrast, human representatives excel in emotional intelligence and context-sensitive responses, which are essential for customer satisfaction and trust (Huang et al., 2024). Consequently, service strategies vary widely across platforms. For instance, JD.com and Shopee adopt a mix of human-only, AI-only, and human–AI collaboration strategies.

While prior research has compared human and AI service performance, the challenge of identifying optimal service modes for different scenarios remains unresolved. Integrating AI to improve organizational efficiency aligns with service-dominant logic (Hofmann et al., 2024; Krüger et al., 2024) and emphasizes key principles such as service excellence (Huang & Rust, 2018, 2022), value co-creation (Polese & Guazzo, 2021; Polese et al., 2022a, b; Sundaresan et al., 2023), transparency (Polese et al., 2022a, b), and human–AI interactions (Le Dinh et al., 2022). Existing studies have explored areas such as chatbot acceptance (Li et al., 2024; Mayr et al., 2024), consumer trust (Glikson & Woolley, 2020), emotional disconnection (Sands et al., 2021), and service coordination (Legros & Jouini, 2019). However, significant gaps persist in understanding how to adapt service modes to specific scenarios, particularly by integrating AI decision-making into service operations.

This study examines AI involvement strategies—AI-only, human-only, and human–AI—through agent-based simulation modeling complex online customer service interactions. Simulations enable continuous adjustments to AI algorithms and workflows, dynamically evaluating strategy effectiveness. Unlike empirical or mathematical models, simulations offer precise control over experimental variables and integrate consumer behavior with organizational decision-making within a dynamic framework (Rand & Rust, 2011).

The article proceeds as follows: "Literature review" section reviews relevant literature. "Simulation settings" and "Agent designs" sections detail the simulation setup and agent design, while "Agent interaction logic" section outlines the interaction logic among agents. "Simulation models" and "AI-involvement strategies in different scenarios" sections present model analyses and strategic decision-making processes. "Competitiveness among e-tailers" section evaluates the impact of competition, and "Discussions" section concludes with key implications.

Literature review

This study explores AI service quality within the context of human–AI interaction. IT-enabled service quality and user satisfaction are fundamental to understanding customer–technology relationships (Sørum et al., 2012). Chatbots exhibiting qualities such as intelligibility, reliability, responsiveness, assurance, and interactivity have been shown to enhance consumer satisfaction, promoting continued usage (Li et al., 2021). In online retail, chatbots add both extrinsic and intrinsic value to customer service, driving higher levels of customer satisfaction (Chen et al., 2021; Haupt et al., 2023). While prior research extensively examines the impact of AI on service quality and consumer satisfaction, limited attention has been given to how platform e-tailers can strategically deploy AI to optimize service delivery. Most studies focus solely on AI's isolated effects, neglecting its role in broader competitive service strategies.

This research also engages with AI anthropomorphism. Studies have analyzed the motivations and outcomes of anthropomorphic chatbot features, which mimic human style and behavior (Crolic et al., 2022). Such features are shown to foster customer trust (De Visser et al., 2016), improve transaction outcomes, and enhance revenue elasticity (Schanke et al., 2021). Visual anthropomorphic cues help mitigate negative company perceptions (Pavone et al., 2022), increase consumers' sense of social presence, and boost engagement (Schuetzler et al., 2020). While these studies focus on AI anthropomorphism's effects on consumers, this research investigates its strategic integration by platform e-tailers—an area that remains underexplored.

Furthermore, this study situates AI within organizational contexts, focusing on its potential to enhance service delivery efficiency (Hofmann et al., 2024; Krüger et al., 2024; Sidlauskiene et al., 2023). Key topics include establishing service dominance (Huang & Rust, 2018, 2022), fostering value co-creation (Polese & Guazzo, 2021; Polese et al., 2022a, b; Sundaresan et al., 2023), ensuring AI system transparency (Polese et al., 2022a, b), and implementing effective human–AI interactions (Le Dinh et al., 2022). While chatbots excel in efficiency and consistency, they often lack the nuanced communication skills required for complex interactions, raising questions about their suitability in certain service contexts (Wirtz et al., 2018). E-tailers use chatbots to reduce costs and enhance customer service (Cheng & Jiang, 2021), but the quality of AI interactions remains a critical factor for consumer satisfaction (Schuetzler et al., 2020), with communication agility being key to performance (Wang et al., 2022). Despite advancements, gaps remain in understanding how AI chatbots and human representatives jointly influence consumers and e-tailers across different service environments. Research is needed to integrate consumer characteristics with AI deployment strategies.

Recent studies highlight the growing importance of human–AI collaboration in service delivery (Huang & Rust, 2022). Intelligence augmentation, enhancing human decision-making through AI, is emerging as a priority in information system research (Jain et al., 2021). Collaborative efforts between humans and AI can significantly boost organizational performance by leveraging their respective strengths (Fügener et al., 2021; Vorobeva et al., 2022). Effective coordination rules are essential for seamless collaboration (Sowa et al., 2021). For example, when chatbots fail to resolve consumer inquiries, smooth transitions to human representatives are crucial (Castillo et al., 2021). Such synergies, where AI complements rather than replaces human capabilities, have the potential to improve service outcomes (Davenport et al., 2019). However, there remains a lack of comprehensive analysis comparing AI-only service environments with those involving human–AI collaboration. Additionally, optimal strategies and conditions for effective human–AI collaboration are underexplored.

Simulation settings

AI is increasingly taking over or complementing tasks traditionally performed by humans (Huang & Rust, 2022). However, further investigation is needed to determine how chatbots can be optimally deployed in online customer service. This involves establishing logical frameworks and evaluating service efficiency across different strategies. This study builds on existing research by quantifying chatbots' levels of anthropomorphism and distinguishing their capabilities from human representatives. These distinctions enable an exploration of how human-only, AI-only and human–AI collaboration strategies affect both e-tailers and consumers, providing practical insights for managers considering AI in customer service.

Research methodology and simulation platform

Agent-based modeling and simulation (ABMS) is an effective method for analyzing decision-making in complex systems, such as online customer service, where tasks and relationships are multifaceted (Macal & North, 2010). ABMS predicts interactions under varying conditions (Macal & North, 2010), making it ideal for assessing the impact of AI strategies on both retailers and consumers. Each agent operates with specific goals and adapts based on interactions, enabling the creation of detailed virtual environments that simulate diverse human–AI interactions, consumer needs, and behavioral patterns—capabilities that surpass those of empirical modeling methods (Rand & Rust, 2011).

This approach allows the evaluation of various service strategies, from human-only to AI-only and human–AI collaboration, across different scenarios to assess their effectiveness. ABMS models are scalable and flexible, allowing continuous optimization of AI algorithms and service workflows. Unlike mathematical or empirical models, which often rely on oversimplified assumptions or lack dynamical integration of consumer behavior and organizational strategies, ABMS provides a controlled environment for iterative experiments and precise adjustments, offering a comprehensive understanding of how consumer behavior aligns with organizational decision-making (Fioretti, 2012).

In comparison to techniques like Monte Carlo simulations, which focus on randomness and risk assessment, ABMS is better suited to capture the complexity of agent interactions and emergent macro-level patterns. Contemporary tools like AutoGPT, which leverage LLMs for complex tasks, lack the controllability and reproducibility needed for multi-agent simulations and are more suited for task execution than for modeling the causal relationships between agent behaviors and emergent system patterns.

ABMS, with its transparent and controllable modeling framework, is ideal for exploring system performance under varying service strategies through controlled rule settings and agent interactions. This study employs ABMS to simulate interactions between human and AI agents, focusing on the impact of different service strategies on macro-level outcomes such as cost efficiency and service quality. This simulation encompasses decision-making rules for agents, dynamic interactions, and system evolution over time. Given these requirements, ABMS is the most suitable tool for this study, emphasizing agent interactions and system dynamics. The construction of the ABMS-based simulation model is illustrated in Fig. 1.

The simulations employ NetLogo 6.2.1, a multi-agent programmable modeling environment developed by Uri Wilensky.[1] Recognized for its advanced simulation capabilities, NetLogo offers a comprehensive model library and is widely used in algorithm design for human–computer interaction (Doryshin & Zamyatina, 2024), information system design (Hakim et al., 2024), online transaction services (Zaffar et al., 2024), traffic scheduling optimization (Sanogo et al., 2024; Vo et al., 2016), and environmental management (Carbo et al., 2017). NetLogo's high-level abstraction language and integrated visualization tools streamline development and support real-time simulation, making it ideal for rapid, iterative model validation. In comparison, Python requires the integration of multiple libraries, such as NumPy and Matplotlib, for visualization, which complicates development and hinders real-time performance. Furthermore, NetLogo's BehaviorSpace tool enables efficient parameter space sampling and batch processing, enabling detailed exploration of how parameter combinations affect system behavior. This study utilizes BehaviorSpace to conduct extensive simulation experiments, analyzing the influence of varying parameters on system dynamics.

Overall procedure

The simulation process unfolds in several stages, as illustrated in Fig. 2. Initially, e-tailer, customer service, and consumer agents are initialized to create the simulation

[1] https://ccl.northwestern.edu/netlogo/index.shtml

Fig. 1 ABMS model construction procedure

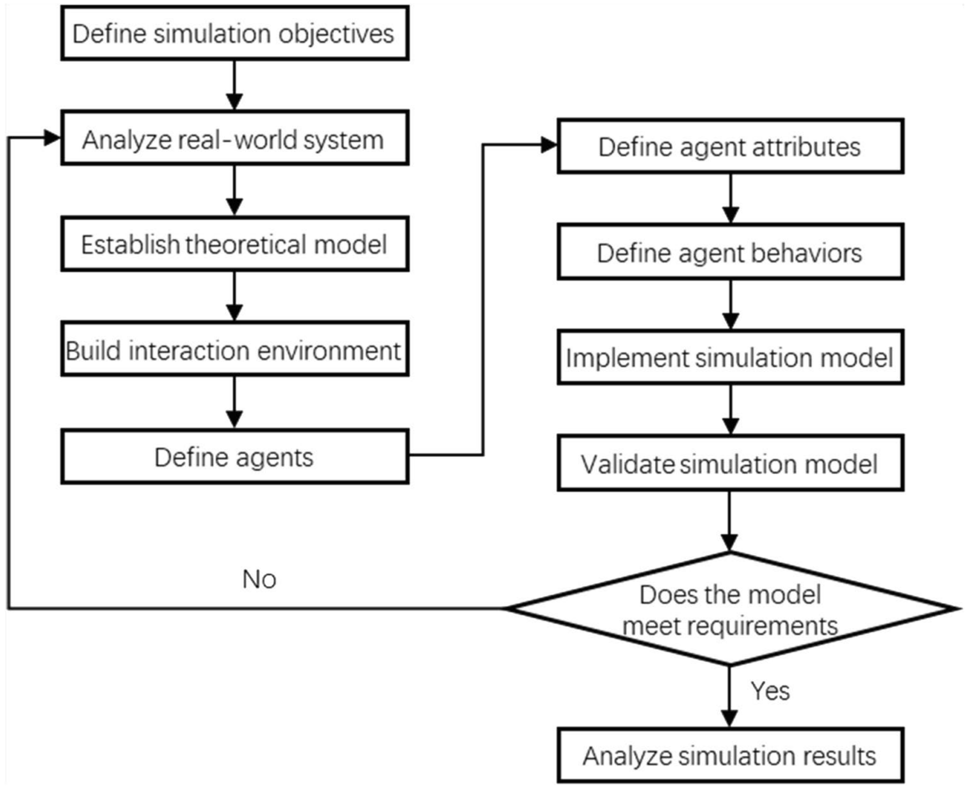
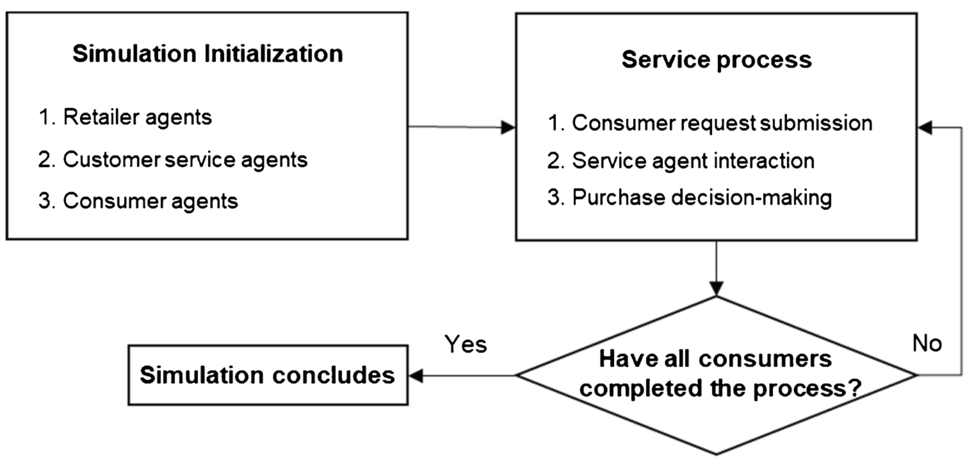


Fig. 2 Simulation procedure



environment. Each e-tailer agent is assigned a service strategy, involving either a human representative, an AI chatbot, or both. Consumer agents then submit requests through a hypothetical e-commerce platform, where customer service agents respond via an online chat system. Based on their satisfaction with the service, consumer agents decide whether to proceed with a purchase. The simulation concludes after all consumer agents complete their respective service interactions. Appendixes provide the NetLogo code used for the simulations and include a link to a supplementary video demonstrating the process.

To ensure validity, the study adopts a multi-dimensional approach to parameter selection, design, and simulation execution. Parameters are established through a comprehensive literature review and real-world service analysis, aiming to develop a realistic model of AI involvement. The chosen parameter values are grounded in theoretical analysis and empirical evidence, ensuring logical consistency and practical relevance. Detailed scenario analyses further validate these settings. To enhance the stability and reliability of the results, outcomes from 30 repeated simulations are averaged, providing robust and consistent data for analysis.

Model assumptions

To address key research questions, the simulations rely on simplified assumptions that focus on essential aspects of service interactions while abstracting away complexities (Fioretti, 2012; Rand & Rust, 2011). Assumptions serve two primary purposes in modeling: (a) increasing analytical tractability and (b) clarifying the scope and applicability of the results (Hannah et al., 2020). The assumptions underpinning the model are summarized in Fig. 3 and elaborated below. A detailed exploration of service interactions is provided in "Agent interaction logic" section.

A1: Homogeneous product focus Each consumer decision pertains to the same product, isolating the effects of service quality on purchasing behavior. This eliminates variability introduced by product differences, enabling a focused analysis of how service interactions influence consumer choices.

A2: Single request with iterative interactions Each consumer submits one request and engages in multiple interaction rounds (each lasting one unit of time) with either an AI chatbot, a human representative, or both. This reflects real-world scenarios where inquiries often involve several exchanges to resolve complex issues (Tezcan & Zhang, 2014).

A3: Progressive request resolution The likelihood of resolving a consumer's request increases with each interaction round. This iterative process leverages accumulating information to refine response quality and better address consumer needs.

A4: Uniform human service capabilities All human representatives have equivalent service capabilities, represented by an average performance level. This simplification facilitates a direct comparison with AI service capabilities, excluding individual variations in human performance.

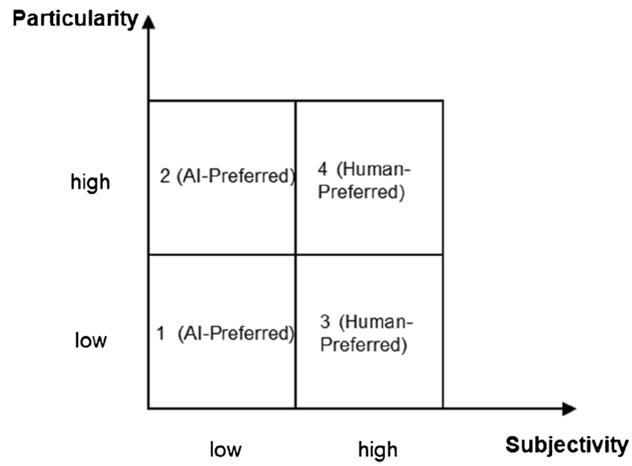


Fig. 4 Segmentation of consumer requests

A5: Agent transparency and consumer neutrality Service agent identities are transparent, aligning with regulations like the EU Artificial Intelligence Act, which mandates transparency for chatbot usage (EU, 2024). Consumers are neutral regarding the agent type (human or AI), eliminating biases in service evaluation.

A6: Exclusion of external factors External factors, including industry-specific characteristics, have no impact on service quality. This isolates the internal dynamics of service interactions for focused analysis.

Classification of consumer requests

Consumer requests vary in complexity for both AI chatbots and human representatives. The study classifies these

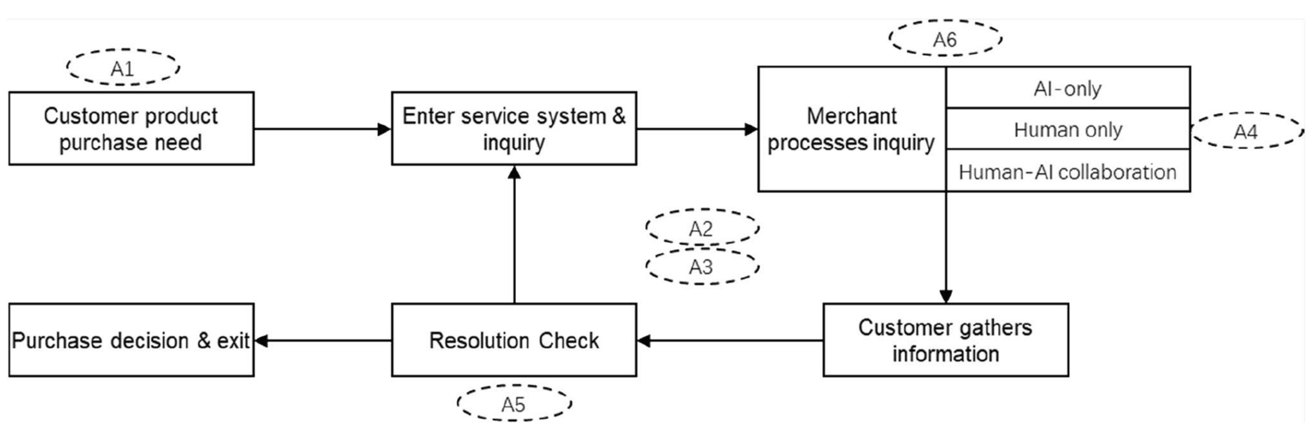


Fig. 3 Service process and associated assumptions (A1–A6)

requests using the theory of task complexity, which considers factors like the number, relationships, and variability of task components (Funke, 2010). Any feature that increases information load, diversity, or variability adds to the complexity of a task.

Both AI chatbots and human representatives have strengths in handling requests of different complexity levels. Fig. 4 classifies consumer requests into four quadrants based on two dimensions: *particularity* and *subjectivity*. *Request particularity* refers to how unique or uncommon a request is among consumer inquiries. Frequently asked questions have low particularity, while rarely asked questions exhibit high particularity. Since AI chatbots are trained on historical data, they tend to perform better at addressing frequently asked questions. *Request subjectivity* measures the extent to which a request involves personal feelings, tastes, and opinions about a product. High subjectivity often requires nuanced, empathetic responses, an area where human representatives excel.

In quadrants 1 and 2, where questions are both low in subjectivity, AI chatbots perform better due to their data-driven responses. For instance, AI chatbots are more effective when questions are low in both particularity and subjectivity (quadrant 1) or high in particularity but low in subjectivity (quadrant 2). However, in quadrants 3 and 4, where questions involve higher subjectivity, especially when combined with high particularity (quadrant 4), human representatives are more effective.

Consumers generally prefer AI chatbots for basic, repeatable tasks in quadrant 1 (low subjectivity, low particularity) but favor human representatives for complex, emotional, or unique inquiries in quadrant 4 (high subjectivity, high particularity). Though less apparent, consumers often believe AI chatbots are better suited for handling requests in quadrant 2 (low subjectivity, high particularity), while human representatives are preferred in quadrant 3 (high subjectivity, low particularity) (Xu et al., 2021).

Previous studies demonstrate that AI chatbots often struggle with addressing unique and subjective questions due to inherent limitations in their problem-solving algorithms (Castelo et al., 2019; Longoni et al., 2019). Even advanced LLMs continue to face challenges related to emotion comprehension (Mitchell & Krakauer, 2023), information pertinence (Forbes, 2023), and knowledge bases (Leggatt & Riva, 2023). These deficiencies are particularly noticeable in e-commerce settings, where the relevance and trustworthiness of information are crucial. Consequently, the level of subjectivity in a customer request becomes a critical factor in determining whether an AI chatbot or a human representative is better suited for the task.

Agent designs

Consumer agents

Consumers aim to maximize satisfaction by assessing a product's value based on the service received and making purchasing decisions (Yuan & Hwarng, 2023). They initiate purchase demands and seek additional product information through customer service interactions. Research indicates that access to information is crucial for consumers when making online purchases (Lei et al., 2022), and online chat positively affects conversion rates (Sun et al., 2021). Throughout the process, consumers evaluate the service by considering whether their needs are met and the time spent.

Purchase demand Purchase demand (PD) refers to a consumer's initial willingness to buy a product before receiving any service, indicating the urgency to fulfill a need. In the simulation, PD ranges from 0.1 to 1, with values from 0.1 to 0.5 representing low purchase demand and values from 0.6 to 1 indicating high purchase demand. This study employs discrete settings to observe the effects of demand changes.

Request subjectivity Request subjectivity denotes the degree of subjectivity in consumer inquiries (Castelo et al., 2019). The more subjective a question, the harder it is for AI chatbots to answer, while human representatives are more adept at handling such inquiries (Brynjolfsson & Mitchell, 2017; Luo et al., 2019). Requests can be classified as low or high subjectivity, with a proportion of high subjectivity requests represented by β_S.

Time sensitivity Consumers consider both the resolution of their issues and the opportunity cost of the time spent waiting for service (Garnett et al., 2002; Ilk & Shang, 2022). Individuals vary in their sensitivity to time and can be categorized into time-sensitive and time-insensitive groups, with the proportion of time-sensitive consumers represented as β_T. A discrete preference distribution is employed to simplify the information processing required for strategy selection analyses.

Expected resolution time t_0 and maximum tolerance time T Each consumer has an expected resolution time t_0 for a request and a maximum tolerance time T for waiting. Time-sensitive consumers have $t_0 = 2$ and $T = 8$, while time-insensitive consumers have $t_0 = 4$ and $T = 10$. These distinctions highlight differences in consumer expectations and tolerances, where time-sensitive consumers are less accommodating of longer resolution times. The parameters t_0 and T represent relative behavioral tendencies rather than precise time values.

Customer service agents

Online customer service enhances communication between firms and consumers, offering a quicker alternative to delayed online comments. Effective customer service can mitigate negative word-of-mouth and emotional distress following service failures (Strizhakova et al., 2012). The quality of information and interaction style of online agents significantly influence customer perceptions (Köhler et al., 2011; Li et al., 2019).

Each customer service agent possesses an anthropomorphic degree i, reflecting their human-like characteristics. According to Assumption 6, human representatives have $i_H = 1$, while AI chatbots have $0 < i_{AI} < 1$. Human representatives assist one customer at a time, resulting in potential wait times, whereas AI chatbots can assist multiple customers simultaneously, reducing inconvenience. Additionally, chatbots are more cost-effective for an e-tailer to deploy than human representatives.

E-tailer agent

An e-tailer offers online customer service to facilitate purchasing behavior. To maximize profits while controlling costs, the e-tailer aims to convert as many consumers as possible (Sun et al., 2021). The profit function below presents the total profit earned after serving customer requests:

$$\pi(S) = KS - C_{AI} - n_M C_M \tag{1}$$

where K represents the marginal profit per product, S is the sales volume, C_{AI} is the cost of operating the chatbot (including acquirement, development, and maintenance), C_M is the cost of providing human services (including wages, recruitment, training, and related expenses), and n_M is the number of human representatives.

The parameter K reflects product profitability and the relative magnitude of service costs. A lower K value (e.g., 0.01) indicates that selling 100 products covers the operating cost of the chatbot, while 1000 products must be sold to cover the hiring cost of each human representative. Conversely, an average K value (e.g., 0.1) suggests that the required transactions decrease to 10 for an AI chatbot and 100 for a human representative.

Agent interaction logic

Consumers initiate requests to e-tailers for intent assurance after being randomly assigned a purchase demand. Three AI-involvement strategies yield distinct impacts on consumers and e-tailers: the AI-only strategy eliminates wait times for consumers, the human-only strategy provides superior emotional support, and the human–AI collaboration strategy necessitates the implementation of collaborative rules.

Additionally, consumers evaluate service time and may choose to leave if it is deemed excessive. If consumers wait in the queue longer than the expected resolution time t_0, they will exit the interaction without having their requests resolved. Conversely, if their requests are resolved within the expected time t_0, they will be satisfied and likely proceed with purchases. If not, consumers will decide whether to purchase based on their original intentions, considering their maximum tolerance time T. This tolerance time is set by the customers themselves and is influenced by their preferences and types, rather than the nature of the service provided by the e-tailer.

Furthermore, the model assumes that consumers can gradually convey their demands to customer service through repeated interactions, thereby enhancing the quality of responses over time (Tezcan & Zhang, 2014). Consumers' purchase decisions are influenced by both the quality and timeliness of these responses. It is assumed that consumers engage in online platform communication with the primary objective of purchasing, using the interaction to inform their decisions. Communication aimed solely at information gathering, without the intention to purchase, is beyond the scope of this research and discussion. The logical structure of online customer service is illustrated in Fig. 5.

Human–AI collaborative rules

To enhance communication effectiveness, the human–AI collaboration strategy is implemented to handle consumer requests. In this approach, the AI chatbot initially engages with the consumer, providing service. However, if the request is too complex or subjective, the consumer has the option to transfer to a human representative for further assistance. Since AI chatbots may struggle with highly subjective tasks, consumers often choose to escalate requests to human representatives if repeated interactions with AI chatbots fail to resolve the issue or achieve satisfactory results.

The transfer of service is triggered when the chatbot is unable to solve the problem within a set time frame $t\prime$, which is defined as half of the expected resolution time $t_0/2$. This rule ensures that if consumers become impatient due to a lack of resolution in a timely manner, their requests will automatically be escalated to a human representative. This approach balances the efficiency of AI chatbots with the emotional support and complex problem-solving capabilities of human representatives, aiming to optimize service quality and consumer satisfaction.

Consumer satisfaction and purchase intention

Consumer satisfaction is determined by the alignment between perceived service quality and expected service quality, as outlined by the Expectation Confirmation Theory.

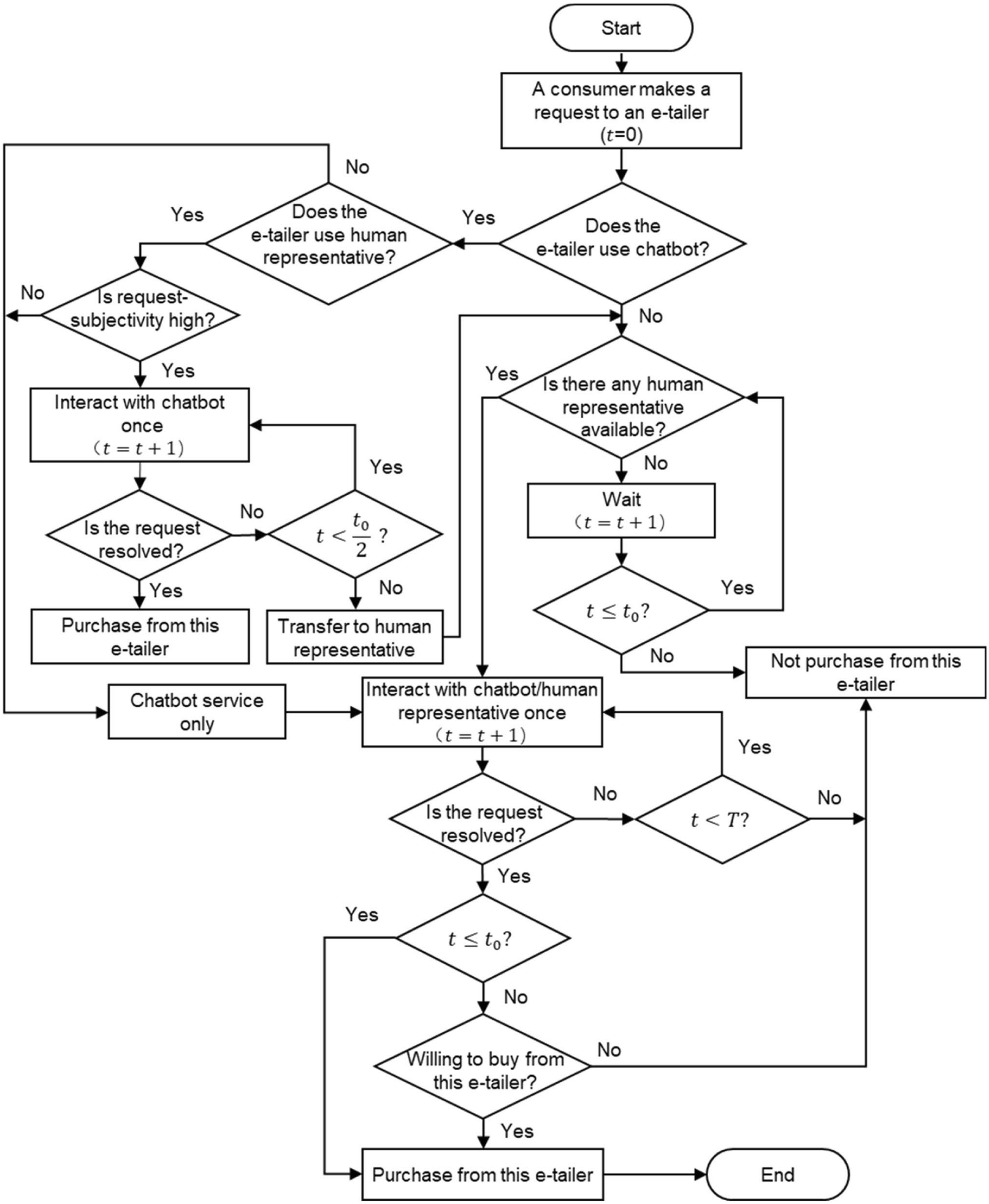


Fig.5 Logical structure of online customer service

Service quality is evaluated along two dimensions: solution time (competence) and emotional support (affection), as proposed by Aaker et al. (2012), Fiske et al. (2007), and Kervyn et al. (2012). Emotional support refers to the degree of warmth and understanding provided by the service agent. Solution time is quantifiable, but emotional support, which correlates with the level of anthropomorphism, is more subjective and harder to measure. In this context, a higher anthropomorphic degree reflects a more human-like interaction, which typically enhances emotional support.

Consumers can discern whether they are interacting with a human representative or an AI chatbot, and their expectations for emotional support from each interaction type typically align with reality. As a result, consumer satisfaction (CS) is primarily influenced by the gap between actual resolution time t_A and expected resolution time t_0, which varies based on the time-sensitivity of each consumer.

If the consumer's request is resolved within the expected time t_0, satisfaction reaches its maximum value $CS = 1$. However, when the actual resolution time exceeds t_0, satisfaction depends on both the delay and emotional support provided by the service. This relationship is captured by the following equation:

$$CS = \begin{cases} 1, t_A \leq t_0 \\ \frac{T-t_A}{T-t_0} \times i, t_A > t_0 \end{cases} \tag{2}$$

where T is the maximum tolerance time, t_A is the actual resolution time, t_0 is the expected resolution time, and i represents the anthropomorphic degree ($i_H = 1$ for human representatives; $0 < i_{AI} < 1$ for AI chatbots).

The satisfaction formula shows that if the actual resolution time exceeds the expected time, consumer satisfaction decreases, depending on how far t_A exceeds t_0 and the level of anthropomorphism in the interaction. The larger the difference between the maximum and actual resolution times $(T - t_A)$, the greater the satisfaction. Conversely, the larger the gap between the maximum tolerance time and the expected resolution time $(T - t_0)$, the lower the satisfaction.

Consumer satisfaction (CS) influences purchase intention (PI), which also depends on purchase demand (PD). The relationship is expressed as

$$PI = CS \times PD \tag{3}$$

where PD reflects the consumer's inherent demand for the product $(0 < PD \leq 1)$. Thus, higher satisfaction directly increases the likelihood of purchase, reinforcing the critical role of timely and emotionally supportive customer service.

Probability decay function

The probability that the consumer's request remains unsolved after each round of interaction with customer service decreases as interaction time progresses. This probability is denoted as $p(t_s)$, where t_s is the service time. According to Assumption 3, the likelihood that the request is still unresolved decreases over time, following a decay pattern:

$$p(t_s + 1) = p(t_s)\alpha \tag{4}$$

where α is the decay coefficient, representing how quickly the request is resolved. The initial probability of the request being unresolved is $p(0) = 1$, and the value of α depends on both the nature (low or high subjectivity) and type of service agent handling the interaction (AI chatbot or human representative), as shown in Table 1.

Consumers generally allocate more time to high-subjectivity requests than low-subjectivity ones. Human representatives typically excel at handling highly subjective requests, while AI chatbots are more efficient with low-subjectivity tasks. This distinction is captured in the decay coefficient α, which varies by both request nature and agent type. The values follow this order: $\alpha_{AI}^L < \alpha_M^L < \alpha_M^H < \alpha_{AI}^H$. This pattern indicates that AI chatbots exhibit higher decay coefficients when handling high-subjectivity requests but outperform human representatives for low-subjectivity tasks. For instance, on the online travel platform Trip.com, AI chatbots independently resolve approximately 78% of flight-related inquiries (Trip.com, 2023). In the simulation, the decay coefficient α for AI chatbots handling low-subjectivity tasks is set to 0.80, with other values calibrated relative to this baseline according to theoretical analysis.

Simulation models

Model 1: Single e-tailer

Model 1 simulates the interaction between consumers and a single e-tailer using various AI involvement strategies. The system comprises one e-tailer, an AI chatbot, human representatives, and n consumers who make requests at an average frequency of λ, following a Poisson distribution. The simulation runs for 3000 time units, equivalent to 3000 h. Demand levels vary across different periods: off-season ($\lambda = 0.33, n = 1000$), normal season ($\lambda = 1, n = 3000$), and peak season ($\lambda = 3, n = 9000$).

Table 1 Decay coefficient values

Request/agent	AI chatbot	Human representative
Low subjectivity	$\alpha_{AI}^L = 0.80$	$\alpha_M^L = 0.85$
High subjectivity	$\alpha_{AI}^H = 0.95$	$\alpha_M^H = 0.90$

Model 2: Multiple e-tailers

Model 2 builds on the single-e-tailer simulation from model 1 by introducing competition among multiple e-tailers. During the peak season, these e-tailers sell the same class of general profit ($K = 0.1$) products, which are similar in price, performance, and quality. For simulation purposes, three types of e-tailers are modeled, each with a distinct AI-involvement strategy: E-tailer 1 uses the AI-only strategy, E-tailer 2 employs the human-only strategy, and E-tailer 3 adopts the human–AI collaboration strategy.

This model incorporates competitive dynamics by simulating how each e-tailer handles customer service requests and how consumers rate their interactions with customer service representatives. After every request, a consumer provides a satisfaction rating for the representative, and each e-tailer evaluates its overall performance by averaging these ratings. As more e-tailers participate, the number of consumers and the average frequency of requests increase, reaching $\lambda = 9$ and $n = 27{,}000$ during the peak season.

In this competitive environment, time-sensitive consumers will either abandon their purchase or switch to

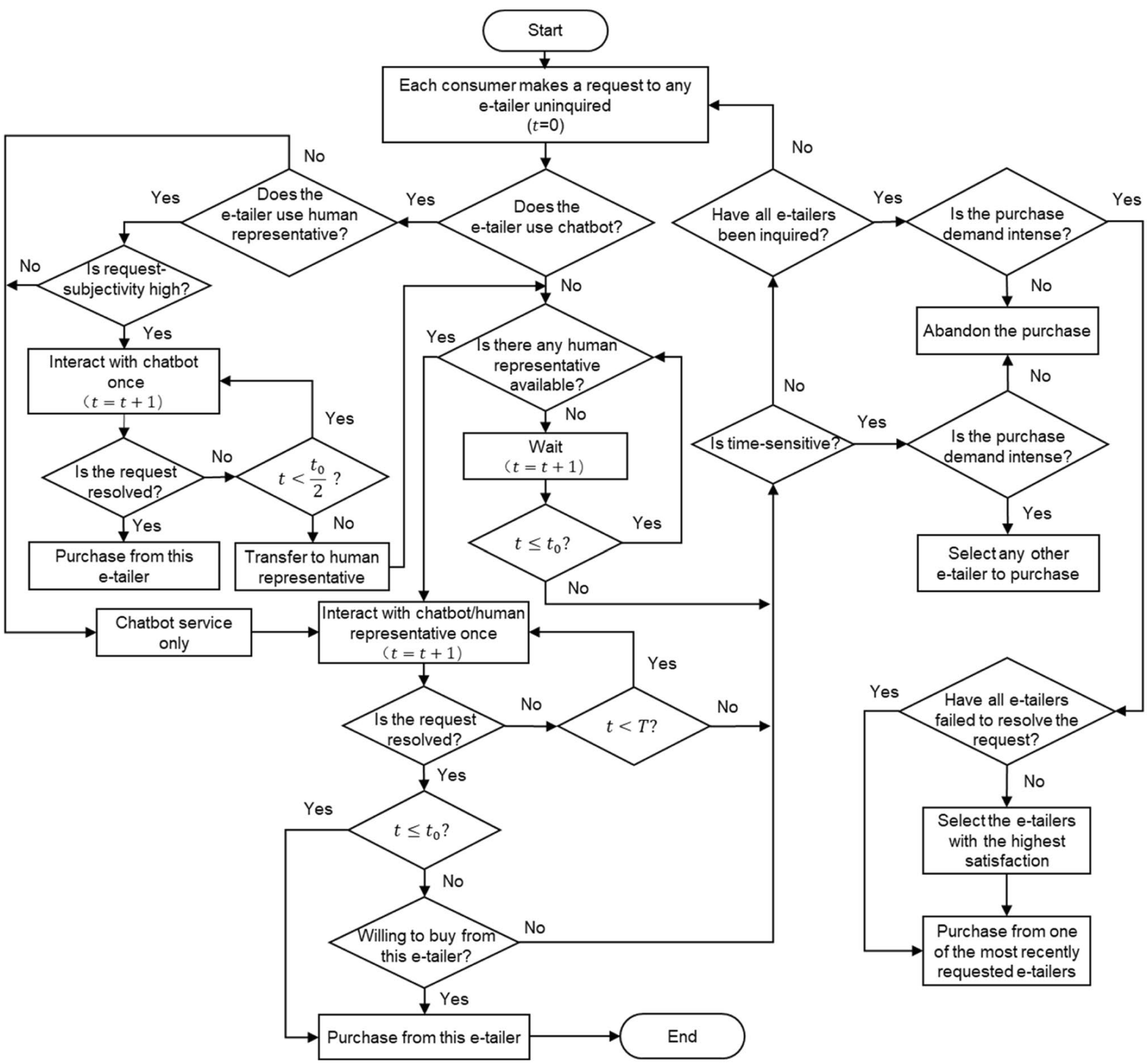


Fig. 6 Extended consumer purchase logic structure

another e-tailer if their request is not solved promptly. In contrast, time-insensitive consumers may try another e-tailer before deciding whether to complete their purchase. If they choose to proceed with the purchase, they will select the e-tailer they are most satisfied with or the one they interact with most recently. Fig. 6 depicts this extended logic structure.

AI-involvement strategies in different scenarios

The study examines AI-involvement strategies along two dimensions: request subjectivity (denoted as β_S) and the proportion of time-sensitive consumers (denoted as β_T). Based on the high and low levels of these dimensions, four typical service scenarios are formed, as shown in Fig. 7:

- *Scenario 1* (*Low-Low*): low-subjectivity and low-sensitivity ($\beta_S = 0.2, \beta_T = 0.2$).
- *Scenario 2* (*Low–High*): low-subjectivity and high-sensitivity ($\beta_S = 0.2, \beta_T = 0.8$).
- *Scenario 3* (*High-Low*): high-subjectivity and low-sensitivity ($\beta_S = 0.8, \beta_T = 0.2$).
- *Scenario 4* (*High-High*): high-subjectivity and high-sensitivity ($\beta_S = 0.8, \beta_T = 0.8$).

The assigned values differentiate typical scenarios for analysis.

In each scenario, e-tailers implement different AI-involvement strategies that affect the deployment of human representatives and AI chatbots. Consumers interact with online customer service following the logic in Fig. 5. The strategies are evaluated across three demand periods: off-season ($\lambda = 0.33, n = 1000$), normal season ($\lambda = 1, n = 3000$), and peak season ($\lambda = 3, n = 9000$). Additionally, two product

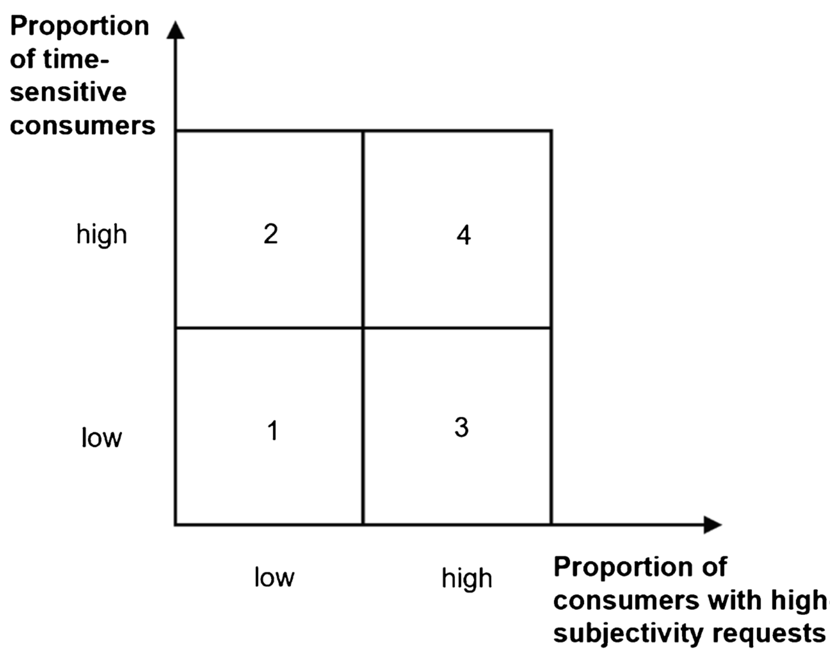


Fig. 7 Service scenarios

Table 2 Parameter default values

Parameter	Value(s)	Description
t_0	2; 4	Expected resolution time: 2 for time-sensitive consumers and 4 for time-insensitive consumers
T	8; 10	Maximum tolerance time: 8 for time-sensitive consumers and 10 for time-insensitive consumers
PD	(Random(10) + 1)/10	Purchase demand: a random value between 0.1 and 1
i_{AI}	0.5	Chatbot anthropomorphic degree: 0.5
n_M	[0, 20]	Number of human representatives: ranges from 0 to 20
C_{AI}	1	Operating cost of chatbot: unit cost of 1
C_M	$10n_M$	Total cost of human representatives: each costs 10 units

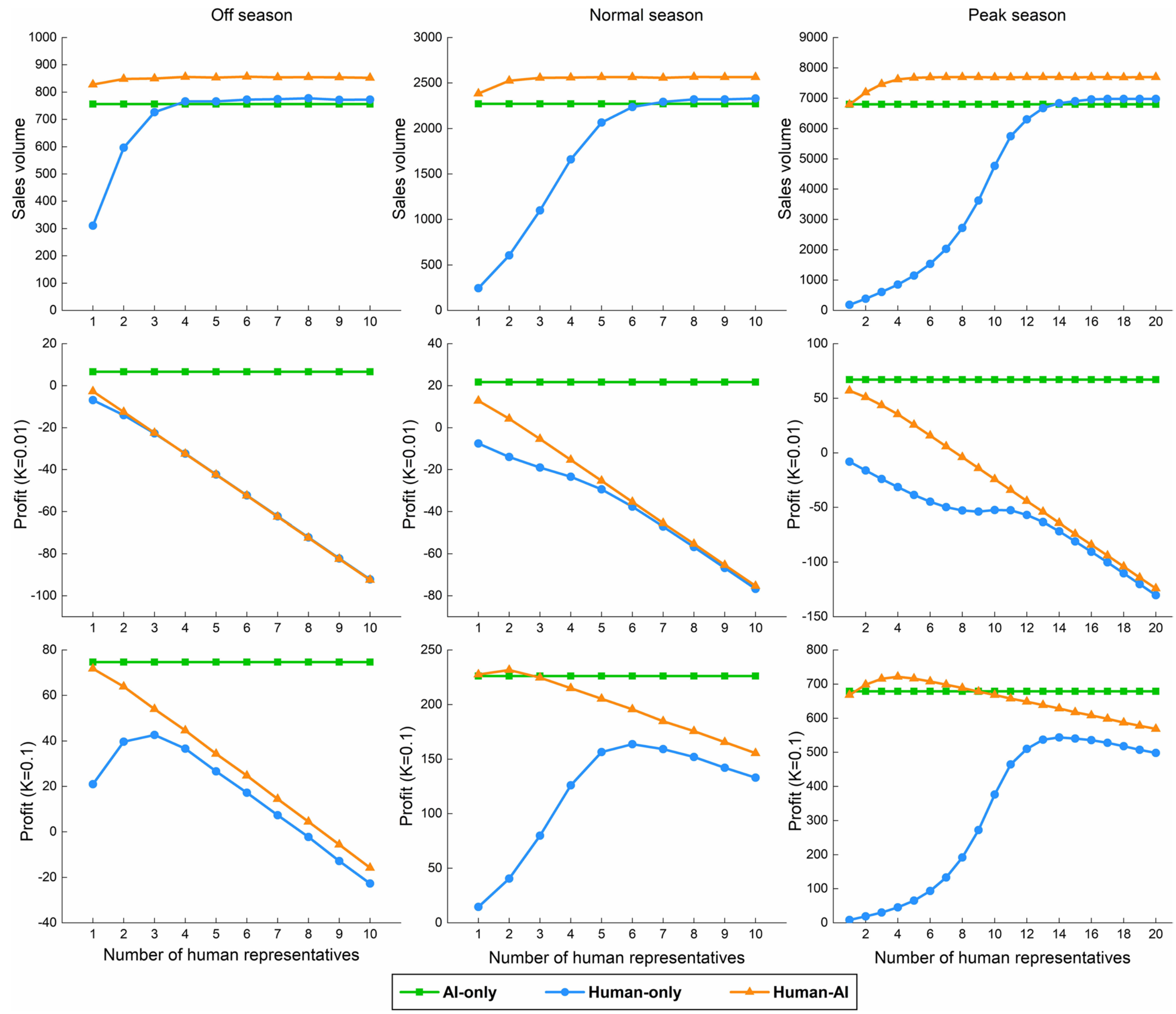


Fig. 8 Changes in sales and profit with the number of human representatives in Scenario 1

types with different marginal profit levels ($K = 0.01$ and $K = 0.1$) are considered. These parameter settings reflect the relative differences in demand across the seasons. To ensure robustness, average values are calculated from 30 repeated simulations. Table 2 presents the default values for the simulation parameters, and Figs. 8, 9, 10, and 11 illustrate the simulation results.

In Scenario 1 (Low-Low), adding human representatives initially boosts sales, but the effect plateaus beyond a certain point, indicating an optimal staffing threshold. Human representatives, with their interpersonal communication skills, eventually surpass the AI-only strategy in sales performance. However, beyond the optimal threshold, additional staff yields no significant gains.

While AI chatbots efficiently handle simple tasks, human representatives outperform in scenarios requiring interpersonal communication and complex problem-solving. A collaboration strategy that integrates both an AI chatbot and human representatives achieves higher sales by leveraging AI's efficiency and human flexibility to meet diverse consumer needs. During high-traffic periods, such as the peak season, e-tailers must increase human staffing to maintain or improve sales, as human services require more staff to compete with AI services.

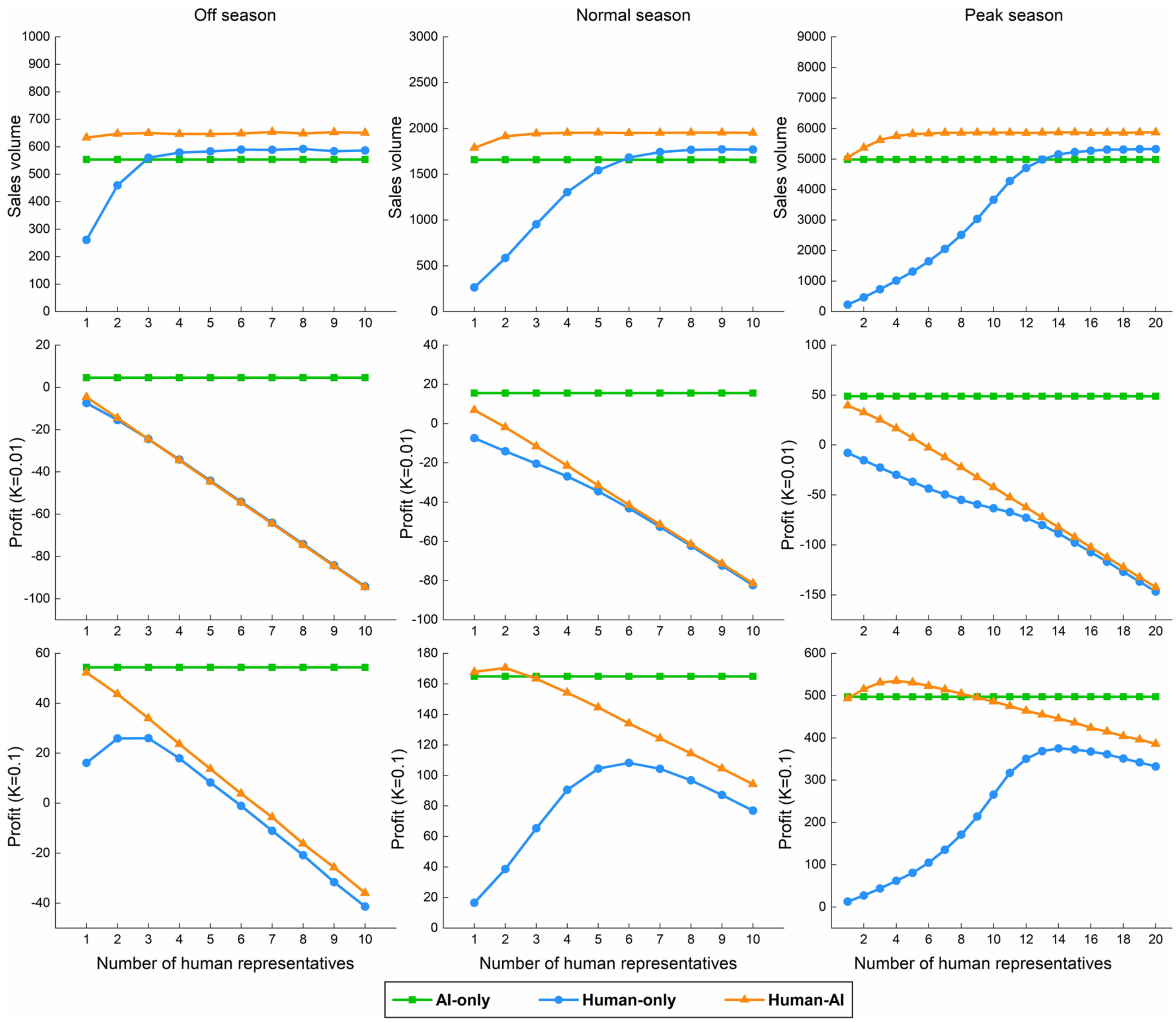


Fig. 9 Changes in sales and profit with the number of human representatives in Scenario 2

In Scenario 2 (Low–High), the AI-only strategy consistently optimizes profit across all seasons for low-margin products ($K = 0.01$). This is due to AI's ability to reduce cost while efficiently handling simple requests, a key advantage for low-margin products.

For high-margin products ($K = 0.1$), the strategic choice varies. During the off-season, AI-only customer service is optimal. In the normal season, a human–AI collaboration with a few human representatives yields the highest profit. In the peak season, a collaboration strategy with four human representatives becomes necessary to handle increased customer requests.

In Scenario 3 (High-Low) and Scenario 4 (High-High), the human–AI collaboration strategy consistently outperforms other approaches in terms of sales, and profit, regardless of the season. Human intervention is essential for resolving complex issues, which AI alone cannot manage effectively. As traffic increases from the off-season to the peak season, more human representatives are needed to handle complex requests. However, AI involvement still contributes by managing simpler tasks, allowing human representatives to focus on more intricate issues.

The presence of time-sensitive consumers negatively impacts sales and profit, particularly under the human-only

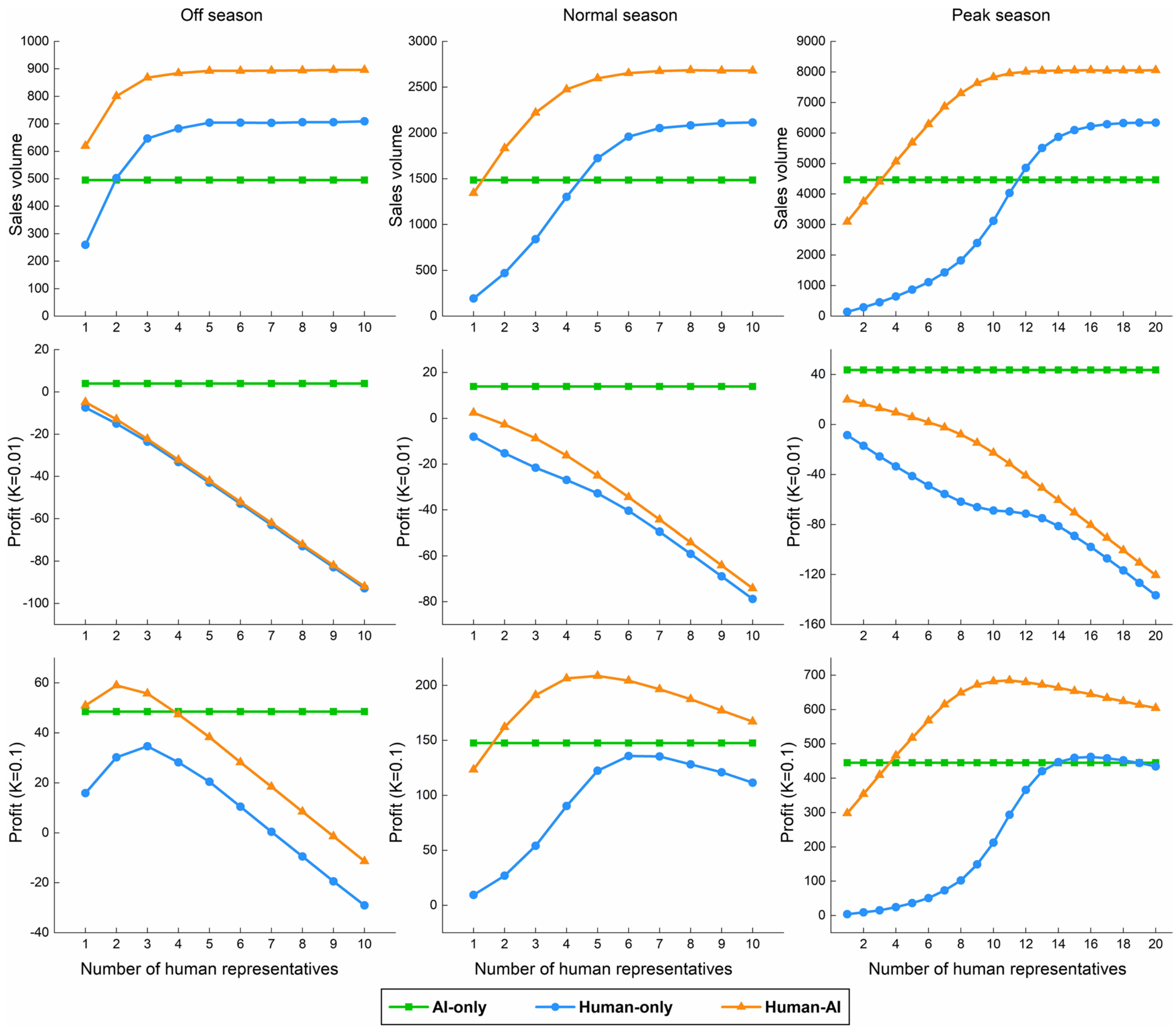


Fig. 10 Changes in sales and profit with the number of human representatives in Scenario 3

or human–AI collaboration strategies, as these consumers prioritize quick responses over service complexity. Despite this, the number of required human representatives remains relatively unchanged, indicating that these consumers' expectations focus on speed rather than resolving complex issues.

Conversely, the frequency of high-subjectivity requests significantly influences staffing needs. When subjectivity is high, the number of human representatives required for maximizing sales and profit increases, particularly in the human–AI and human-only strategies. The AI-only strategy, however, struggles with handling high-subjectivity requests, underscoring the necessity of human involvement for more complex problem-solving.

Competitiveness among e-tailers

This section explores how different AI-involvement strategies impact the competition among multiple e-tailers in the market. The analysis focuses on market share and consumer satisfaction based on each e-tailer's strategy selection in various situations. To simulate a competitive environment, peak season dynamics are included, and the number of human representatives for human-only and human–AI collaboration strategies is adjusted to maximize profitability. Table 3 presents the required human representatives under different levels of request subjectivity, which has a greater impact on staffing needs than time sensitivity.

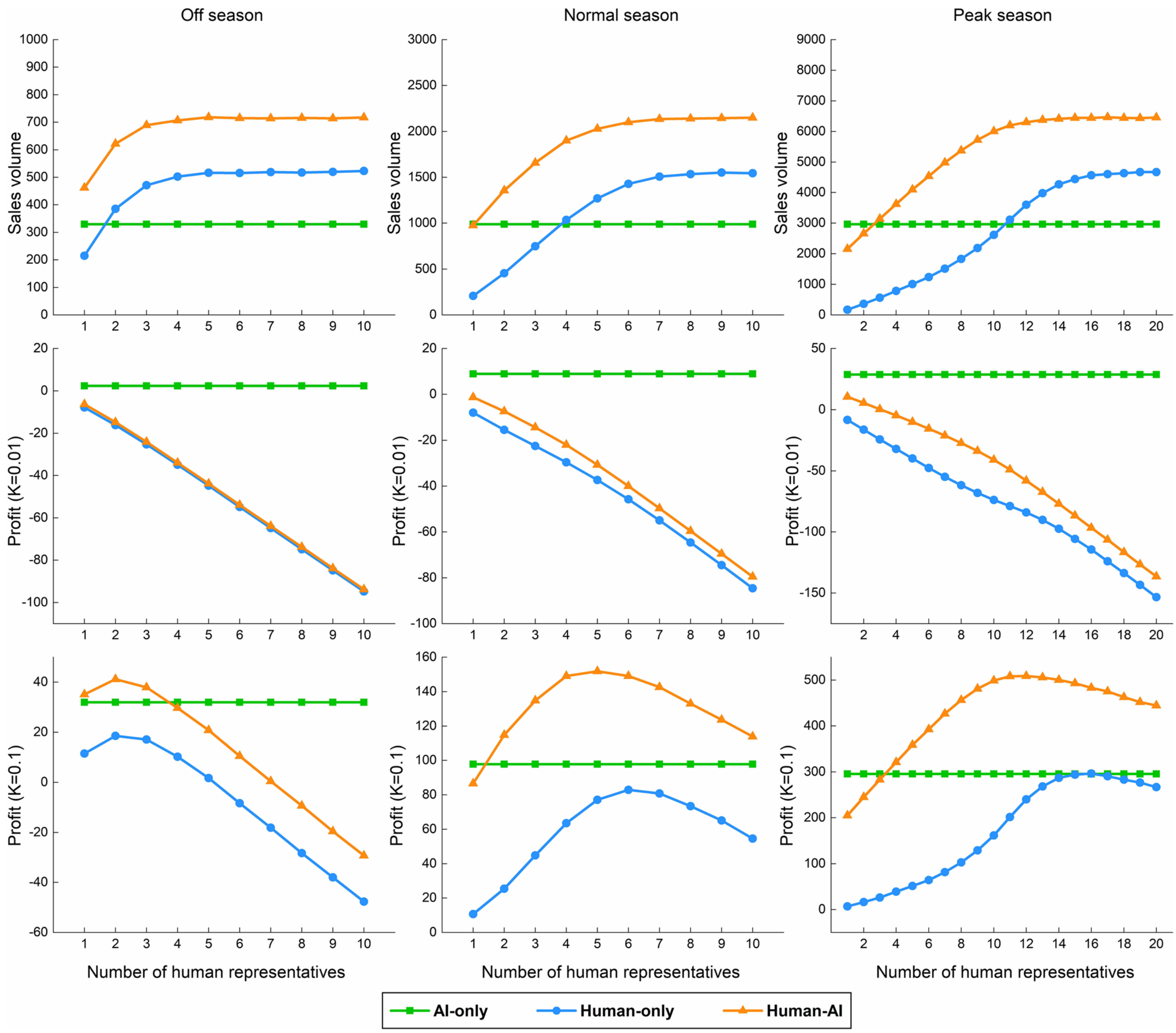


Fig. 11 Changes in sales and profit with the number of human representatives in Scenario 4

Table 3 Human representatives needed

Request subjectivity	E-tailer 1 (AI-only)	E-tailer 2 (human-only)	E-tailer 3 (human–AI)
$\beta_S = 0.2$	/	$n_M = 14$	$n_M = 4$
$\beta_S = 0.8$	/	$n_M = 16$	$n_M = 11$

Consumer time-sensitivity

Adding more human representatives beyond a certain point does not significantly contribute to sales growth and may reduce profitability. However, the effects of consumer time-sensitivity are more context dependent. With a fixed chatbot anthropomorphism degree $i_{AI} = 0.5$, Fig. 12 illustrates how market share, sales volume, and consumer satisfaction vary across two levels of request subjectivity for each e-tailer.

- Low request subjectivity ($\beta_S = 0.2$): When consumer time sensitivity is high, e-tailer 2 (human-only) outperforms e-tailer 1 (AI-only), as human flexibility better addresses time-sensitive needs. However, market share differences among the three e-tailers remain minimal.
- High request subjectivity ($\beta_S = 0.8$): e-tailer 3's human–AI collaboration strategy dominates in both market share and consumer satisfaction, revealing AI's limitations in handling complex requests.

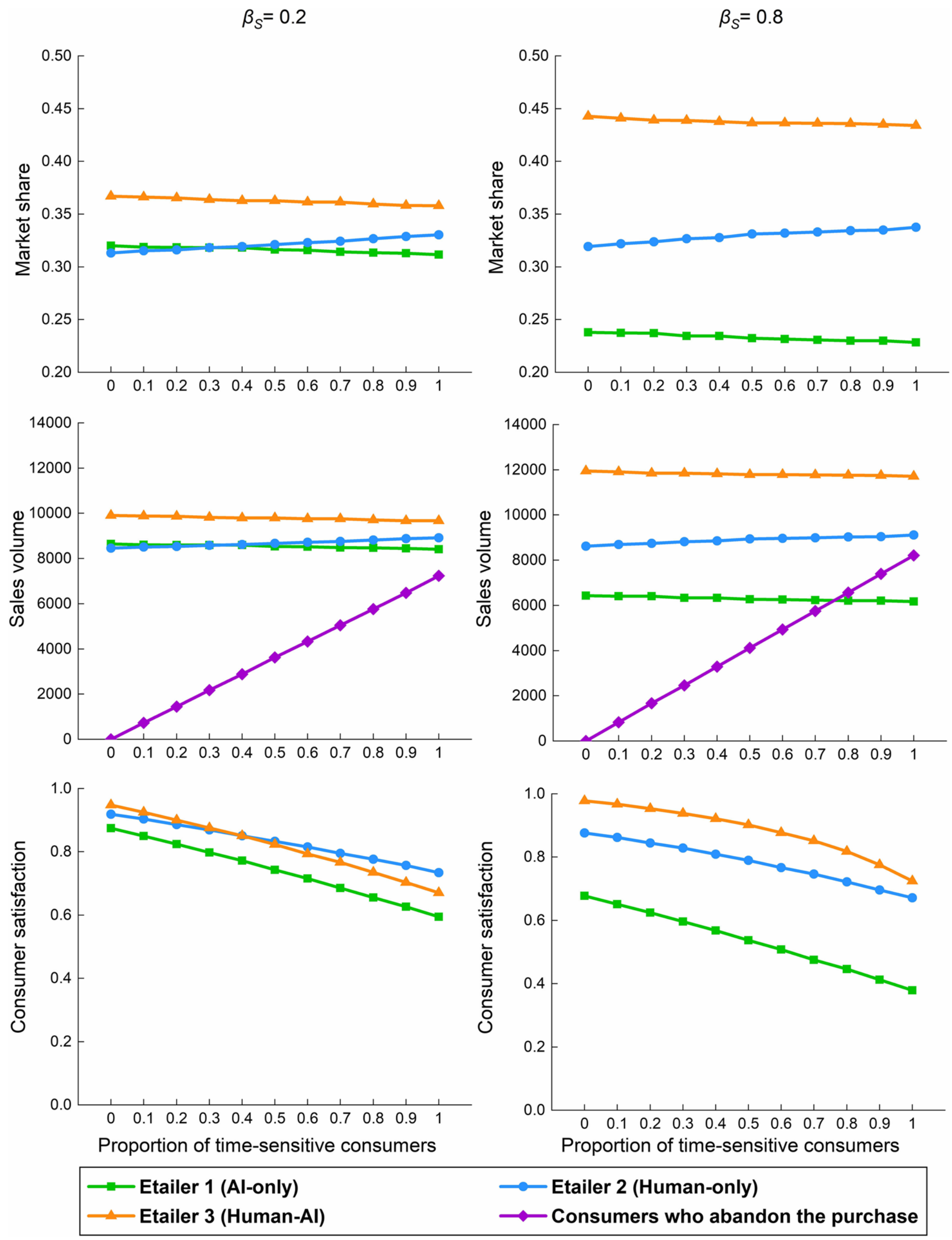


Fig. 12 Impacts of consumer time-sensitivity on e-tailers

As consumer time sensitivity increases, satisfaction decreases, particularly for e-tailer 1 (AI-only) and e-tailer 3 (human–AI collaboration). In high-subjectivity scenarios, e-tailer 3 achieves the highest satisfaction, outperforming e-tailer 2 (human-only) when time-sensitive consumers account for more than 40%.

In summary, the human–AI collaboration strategy handles both high subjectivity and time-sensitive demands more effectively. The AI-only strategy is cost-effective but struggles with complex scenarios, while the human-only strategy excels in time-sensitive cases but lacks the efficiency of human–AI collaboration.

Chatbot anthropomorphism

The degree of chatbot anthropomorphism significantly affects how e-tailers handle high-subjectivity requests, influencing both market shares and consumer satisfaction. Fig. 13 illustrates the effects of anthropomorphism in different service scenarios during peak season.

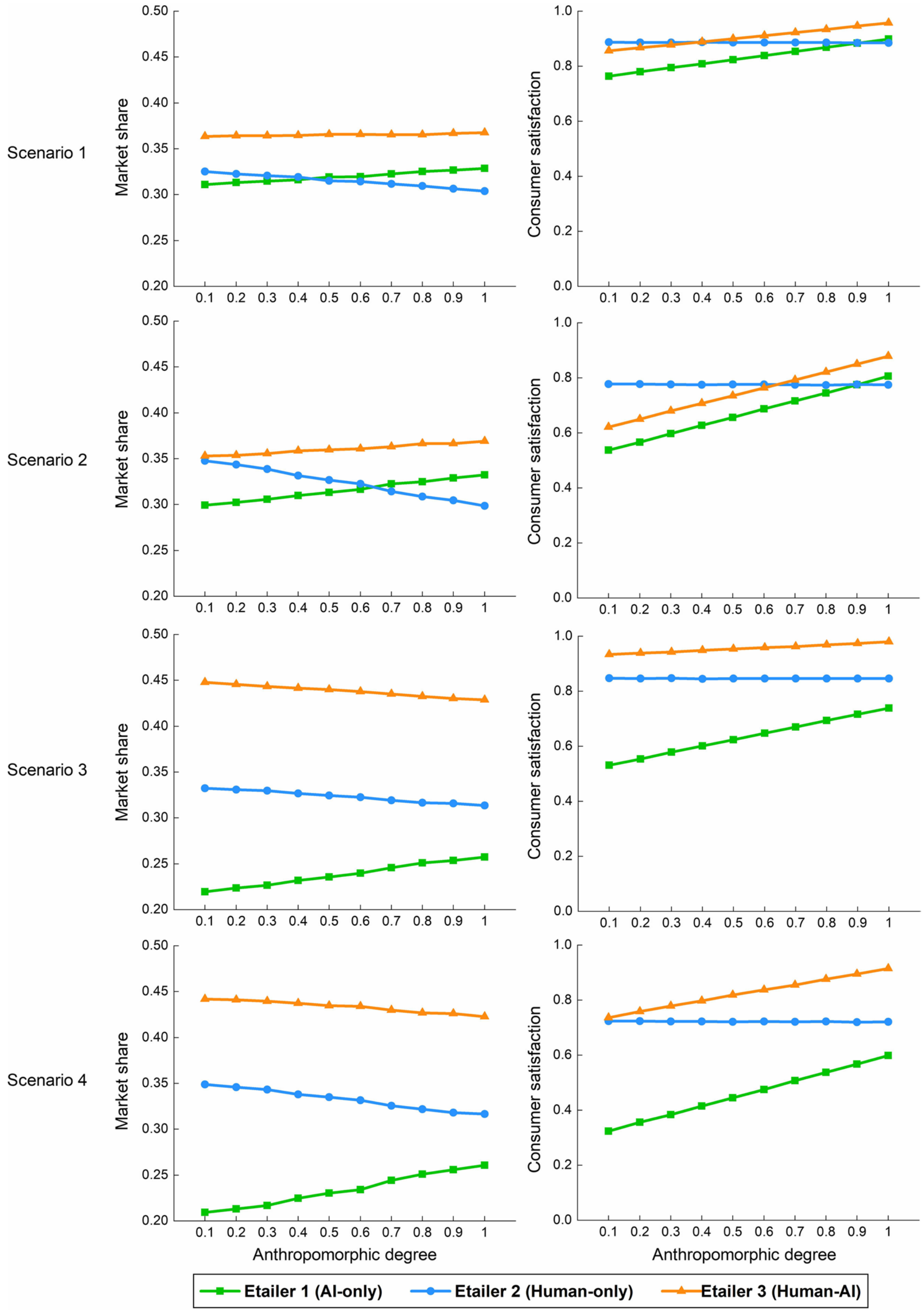


Fig. 13 Impacts of chatbot anthropomorphism on e-tailers

- Low request subjectivity ($\beta_S = 0.2$): Increasing the anthropomorphic degree benefits both e-tailer 1 (AI-only) and e-tailer 3 (human–AI collaboration) in terms of market share, with e-tailer 1 surpassing e-tailer 2 (human-only) as chatbot anthropomorphism improves.
- High request subjectivity ($\beta_S = 0.8$): E-tailer 3 maintains the highest market share, followed by e-tailer 2, while e-tailer 1 struggles to compete effectively.

Consumer satisfaction also improves for AI-involved e-tailers (e-tailer 1 and e-tailer 3) as chatbot anthropomorphism increases. For low-subjectivity requests, anthropomorphic degrees above 0.4 and 0.9 lead to higher satisfaction for e-tailer 3 and e-tailer 1, respectively, compared to e-tailer 2. For high-subjectivity requests, e-tailer 3 consistently achieves the highest satisfaction.

In summary, chatbot anthropomorphism improves the competitive position of e-tailers adopting AI-involvement strategies, with human–AI collaboration being particularly effective in managing complex, high-subjectivity requests. While human-only strategies perform reliably in high-subjectivity scenarios, the combination of human flexibility and AI efficiency yields superior results in a competitive market.

Discussions

The main findings of the research, based on analysis results, are discussed below:

1. Strategy selection and service delivery

This study examines effective strategies for service delivery in AI-involved environments, focusing on settings offering both AI-only and human–AI collaboration options (Fig. 10). Counterintuitively, the AI-only strategy proves optimal for low request volumes and simple tasks, where human representatives are typically expected to provide more personalized service. In such cases, AI's efficiency and cost advantages outweigh the benefits of human involvement. However, as inquiry volumes rise, the human–AI collaboration strategy becomes more effective, demonstrating its adaptability to fluctuating inquiry volumes—even for simpler tasks—by scaling human involvement when necessary.

2. Impact of product characteristics on strategy choice

Product characteristics significantly influence the extent of AI involvement in online customer service (Fig. 9). For low-margin products, the AI-only strategy consistently emerges as optimal across varying levels of consumer demand due to its cost-control advantages. In contrast, for high-margin products, the human–AI collaboration strategy proves more effective in meeting consumer needs for timely and subjective interactions, thereby enhancing demand and elevating service quality.

3. Human–AI interaction management and personnel allocation

The study underscores the importance of managing human–AI interactions and personnel allocation within service operations. Analysis reveals diminishing marginal returns when deploying human representatives alongside AI chatbots (Fig. 8). While increasing the number of human representatives initially boosts sales, exceeding a certain threshold results in diminishing benefits, with additional representatives potentially reducing sales. These findings offer essential insights into optimizing the integration and deployment of AI services within organizations.

4. Managing service agents and consumer interactions

The research examines how variations in consumer request complexity and time sensitivity affect sales and strategic decisions (Fig. 11). High time sensitivity, coupled with stable request complexity, negatively impacts sales and profits without significantly increasing the need for human representatives. Conversely, fluctuating request complexity necessitates adjustments in human involvement. In such scenarios, the human–AI collaboration strategy consistently outperforms other strategies, particularly when handling complex and subjective requests.

5. Insights for competitive markets

The study identifies several counterintuitive findings in competitive markets, offering strategic insights for e-tailers (Figs. 12 and 13). Human-only service outperforms AI-only service in highly time-sensitive, low-subjectivity scenarios. As request complexity increases, the human–AI collaboration strategy rapidly gains market share. Interestingly, in highly time-sensitive contexts, consumer satisfaction with human-only service can exceed that of human–AI collaboration, reflecting a preference for human interaction in specific situations. Meanwhile, AI-only service struggles in complex, time-sensitive environments, failing to drive demand or profit growth. Enhancing the anthropomorphic features of AI chatbots strengthens their strategic advantage, particularly when managing time-sensitive consumers.

Conclusion and implications

The widespread adoption of AI in the service industry has created both opportunities and challenges for businesses (Hohenstein et al., 2023; Krüger et al., 2024; Polese et al., 2022a, b). This study tackles these challenges by modeling online customer service encounters, analyzing optimal AI-involvement strategies across diverse scenarios, and assessing their impacts on e-tailer competitiveness and consumer satisfaction. The findings offer valuable managerial and theoretical implications.

Managerial implications

1. Adapting service strategies based on demand and complexity

In environments with lower demand and simpler tasks, AI-only services are highly effective due to their operational efficiency and cost advantages. E-tailers should adopt the AI-only strategy in such contexts. However, as inquiry volumes grow and requests become more complex or require subjective judgment, integrating human–AI collaboration becomes essential. E-tailers should maintain flexible human resource allocation to adapt to demand fluctuations and prevent mismatched resource deployment. Furthermore, aligning service delivery agents with product characteristics is crucial. For low-margin products, the AI-only strategy helps control costs, while high-margin products benefit from human–AI collaboration, which combines human expertise with AI efficiency to meet consumer expectations for timely and personalized service.

2. Optimizing human–AI collaboration in service delivery

Increasing the number of human service representatives can initially boost sales; however, beyond a certain point, additional staffing yields diminishing returns. The human–AI collaboration strategy optimizes resource allocation by directing complex and subjective requests to human representatives while assigning simpler inquiries to AI agents. Retailers can implement intelligent service scheduling systems to automatically route service requests based on their complexity, ensuring both efficiency and effectiveness in service delivery.

3. Adjusting service strategies in competitive markets

Managers must balance cost efficiency with rapid service delivery while meeting customer expectations. As request complexity rises, the human–AI collaboration strategy demonstrates superior effectiveness in capturing competitive market share. In time-sensitive situations, customers may favor human interactions, prompting managers to tailor service strategies based on complexity and time sensitivity. Enhancing AI's anthropomorphic features can further bridge efficiency and customer experience, particularly in time-critical contexts.

4. Implementing and enhancing AI customer service

Strengthening transparency and compliance is essential in deploying and implementing AI customer service. With growing regulatory scrutiny, such as the EU's Artificial Intelligence Act (EU, 2024), which regulates limited-risk AI systems, e-tailers must clearly disclose AI involvement in consumer interactions or flag AI-generated content. Continuous system performance monitoring and regular consumer feedback assessments are critical to maintaining compliance with regulatory standards and adapting strategies to evolving market conditions.

Theoretical implications

1. Optimal service strategies for AI integration

This study offers valuable insights into optimal service strategies for e-tailers integrating AI, enriching the growing body of literature on AI service engagement and delivery processes (Kaartemo & Helkkula, 2018; Krüger et al., 2024; Polese et al., 2022a, b). By accounting for diverse market, vendor, and consumer characteristics, the research provides actionable guidance on optimizing service delivery in AI-involved environments.

2. Human–AI collaboration in service interactions

The research examines both the optimal conditions and potential pitfalls of human–AI collaborative service interactions. Expanding on prior research on the organizational embedding of human–AI collaboration (Huang & Rust, 2022), it identifies the specific scenarios where this strategy is effective while highlighting circumstances that could lead to its failure.

3. Modeling AI–consumer interaction and human–AI collaboration

This study models AI involvement in consumer encounters and service delivery by incorporating human representatives, AI chatbots, and other agents as integral components of AI-driven service systems (Hofmann et al., 2024). Contributing to service encounter research (Krüger et al., 2024), it offers novel perspectives on the dynamics of non-contact service processes, advancing understanding of AI's role in consumer engagement and the mechanics of human–AI collaboration.

4. Co-creation of service value

The findings deepen understanding of how human–AI collaboration fosters service value co-creation, extending existing work about the organizational benefits of AI (Huang & Rust, 2018, 2022; Polese et al., 2022a, b). This strategy is shown to drive innovation, improve service quality, and contribute to the continuous enhancement of customer experience and organizational performance.

Future research

Several promising directions for future research emerge. First, AI interventions not only reshape interaction patterns between merchants and consumers but also transform the dynamics and value co-creation processes among AI chatbots and human representatives. Exploring these broader effects could provide valuable insights into the evolving nature of service ecosystems. Second, advancements in text mining, such as aspect-based methods and ontologies, present opportunities to enhance AI-driven customer service strategies. Future studies could explore how these technologies improve AI effectiveness in addressing diverse customer needs. Third, integrating simulation-based optimization of operational strategies with empirical analysis of customer service data could advance understanding of AI's role in real-world service environments. Experiments and operational data analytics could validate simulation findings, providing a more comprehensive perspective. Fourth, as AI adoption expands across industries, examining its role in both independent and assisted decision-making in customer services becomes increasingly critical. Understanding AI's transformative impact on decision-making processes and service delivery can yield actionable insights for researchers and practitioners alike. Finally, this study's simulations rely on clearly defined assumptions about service interactions and consumer behavior. Relaxing these assumptions in future research could uncover novel insights by exploring the effects of AI-driven service strategies in alternative application scenarios, thereby broadening the scope of understanding.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12525-025-00821-8.

Declarations

Conflict of interest The authors declare no competing interests.

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